CAS ETH in Machine Learning in Finance and Insurance - Innovation project

Yield Crop Estimation Based on Remote Sensing Data

Project report

05st November 2024

ETH zürich

Blue Marble

Introduction

Problem description

Predicting crop yield is an important task from multiple perspectives. On the global and administrative level it's relevant for food security. Under the impact of growing population and climate change it is expected that globally, food demand will increase by 35% to 56% between 2010 and 2050 while the population at risk of hunger will change from -91% to 30%[1]. On the local level accurate estimation of crop yield helps to select the best season and plants to grow.

There are multiple risk factors that affect the crop yield and that are difficult to manage on the individual level and hence create an opportunity for insurance and reinsurance companies to support and help distribute risk on the national and global level.

The primary aim of this project is to apply machine learning models to satellite images to predict corn crop yield in the USA. The secondary objective is to support the strategic goal of Blue Marble to build knowledge and predictive models that would allow extension of insurance coverage beyond weather risks. As parametric insurance is the main business driver of this investigation, model performance for poor harvest years is of special interest.

Blue Marble is an Impact InsurTech with a mission to bring insurance to the underserved, farming communities. They are present in Latin America, South and South-East Asia and Africa.

[1] van Dijk, M., Morley, T., Rau, M.L. *et al.* A meta-analysis of projected global food demand and population at risk of hunger for the period 2010–2050. *Nat Food* 2, 494–501 (2021). https://doi.org/10.1038/s43016-021-00322-9

Literature discussion

Due to its importance, crop yield prediction is a popular research topic. In recent years various machine learning methods have been applied to the problem. Systematic literature reviews from 2022[2] and 2020[3] showed a growing interest in AI driven methods. According to both studies the most popular architectures for the task are CNN and LSTM.

In the article "Deep gaussian process for crop yield prediction based on remote sensing data." the authors propose the use of histograms as input features into LSTM and CNN models. Due to the popularity of those two architectures and the attractive dimensionality reduction property of histograms it is an attractive proposition as a starting point for future research. For exactly this reason the decision has been made to attempt to replicate machine learning and data models proposed by the authors.

Literature review for this project revealed two additional papers that could be particularly interesting as a future extension due to interesting application of transformers.

- Rad, Ryan. "Vision Transformer for Multispectral Satellite Imagery: Advancing Landcover Classification." Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. 2024 author proposes new attention mechanism designed to work with multispectral images.
- Lin, Fudong, "MMST-ViT: Climate Change-aware Crop Yield Prediction via Multi-Modal Spatial-Temporal Vision Transformer." Proceedings of the IEEE/CVF International Conference on Computer Vision. 2023. Authors develop a multimodal model for crop yield prediction.

[2] Muruganantham, Priyanga, Santoso Wibowo, Srimannarayana Grandhi, Nahidul Hoque Samrat, and Nahina Islam. 2022. "A Systematic Literature Review on Crop Yield Prediction with Deep Learning and Remote Sensing" Remote Sensing 14, no. 9: 1990. https://doi.org/10.3390/rs14091990

[3] *Thomas van Klompenburg, Ayalew Kassahun, Cagatay Catal, "Crop yield prediction using machine learning: A systematic literature review", Computers and Electronics in Agriculture, Volume 177, 2020, 105709, ISSN 0168-1699*

Modeling

High level description

First assumption is that the location of a pixel in an image is not as important as its color. This allows us to reduce dimensions of the data significantly, group pixel values together and work with the counts of pixels i.e. histograms rather than full images themselves.

To make data collection possible within the timeframe of the project further simplifying assumptions is that enough information will be captured at pixel resolution of 60x60 meters and that it's possible to reduce corn season lasting between May and September to three two-month periods that can be represented by the median value of each pixel. It means that there are:

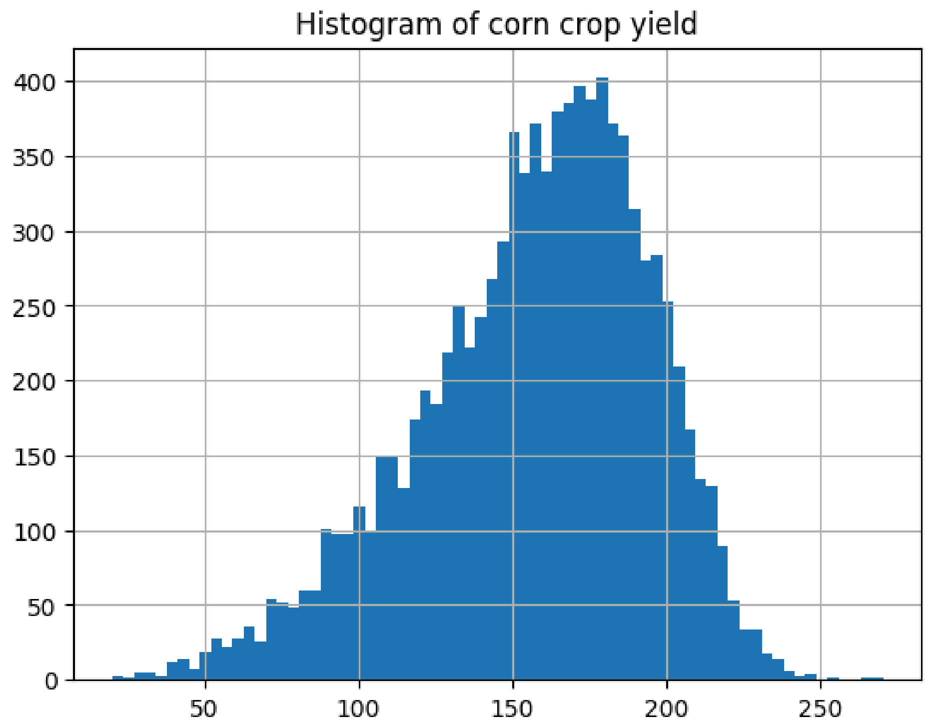
- 3 images per year,
- Each pixel has a resolution of 60 by 60 meters
- Pixel's value is a median value of all images that had less than 35% of cloudy pixels captured by Sentinel2 satellite within each two month period.

Data collection

Labels were obtained from CropNet[4] dataset that was recently published on Hugging Face. The source of the labels is the United States Department of Agriculture and contains information on yearly corn yield measured in bushels per acre for the years 2016-2022. We choose the lowest level of aggregation possible and target predictions on the county level.

The distribution of labels is slightly skewed to the left with mean of 157, standard deviation of 38 and skewness of -0.58. Given that skewness is not significant we have decided not to apply any transformation to the data.

[4] [CropNet/CropNet · Datasets at Hugging Face]()



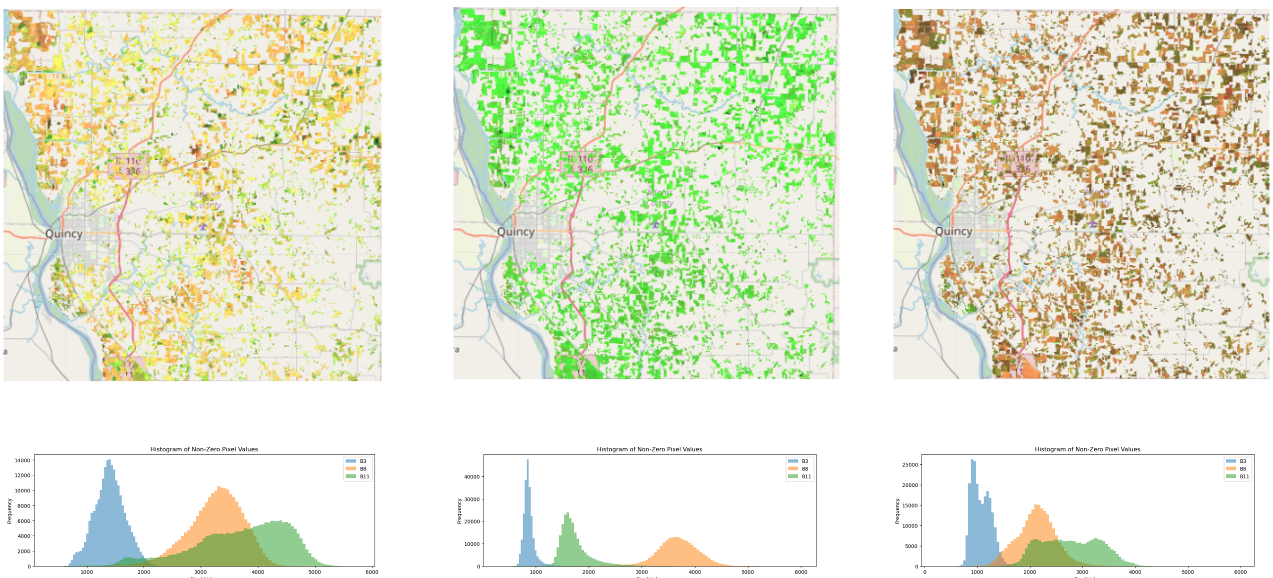
We have collected 28661 Sentinel2 satellite images via google earth engine. To obtain a dataset that is in line with labels, each image is cropped according to the county administrative boundaries based on 2018 census data and pixels representing corn crop according to the USDA National Agricultural Statistics Service. After cropping the images take roughly 80gb of storage space.

The images were transformed into the same amount of histograms. Subsequently all histograms from belonging to the specific county and year have been concatenated. In case one of the three histograms for the specific county and year combination were missing we used an empty histogram as a placeholder, otherwise the sample was discarded.

In total 9578 data points have been prepared for regression. Histograms used for training are based on 9 channels: blue, green, red, red edge 1, red edge 2, red edge 3 and red edge 4 as well as near infrared and water vapor. Each histogram has 60 bins. These parameters were chosen after experimenting with different values. Lower levels lead to poor model performance and going beyond did not provide much improvement while in extreme cases also lead to worse model performance.

Sample satellite images

Below, a sample of three satellite images overlaid with a map of the USA. The images show Adams county in Illinois in 2017. From the left, median of months May and June, July-August and September-October and their corresponding histograms. Images and histograms are visualisations of three channels: green, short wave infrared and near infrared.



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Given that different seasons are clearly distinguishable the initial assumptions about importance of pixel values seem plausible. Perhaps even more so when we consider that each image has 13 channels in total.

Models, training and evaluation

Typical test train split was applied. We set aside 20% of data to use as a test dataset for model evaluation. We split the remainder further into training and validation datasets. Each holding respectively 64% and 16% of the initial data.

Three separate model architectures were implemented for comparison. Simple fully connected multi layer perceptron, LSTM and CNN. No simpler model, like linear regression, has been proposed due to the high dimensionality of the problem.

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General observations

Based on loss function only there is no clear favorite among the three approaches.

MLP has proven to be very flexible and can easily work with a penalized loss function that was used with the intention of improving the fit in the left tail of the distribution. Slightly better results for predicting bad years comes with higher variance on the unseen data.

LSTM architecture has proven to be difficult to work with. Most changes in the model architecture beyond adding an attention layer leads to the vanishing gradients and constant predictions. Having said that, once the model finds the good path beyond the average the model offers the smoothest learning path.

CNN had the advantage of being quite flexible without convergence issues. It has decent tail performance and lower variance in predictions.

Interestingly, introducing a covariate representing information about the state that the county belongs to improved performance of LSTM and MLP. Due to differences in architecture and shape of the inputs the same was not tested on CNN. Before the introduction of state code CNN model was performing marginally better than the other two. With the extra covariate however LSTM took the lead. It generalizes better and performs better in low yield scenarios. The improved model performance with additional covariate indicates that there are other important factors, potentially linked to the geography that are not covered by satellite images.

For brevity only LSTM architecture will be presented in detail. All experiments performed during this project are available for inspection at weights and biases[6] portal. Furthermore github repository[7] contains the codebase necessary to replicate the experiments. Access to both is public.

LSTM model architecture

Model layers:

- 7 stacked LSTM layers with 200 units each, default activation functions
- Additive attention layer with 200 attention units
- Fully connected linear output layer

[6] https://wandb.ai/t-skorkowski/blue-marble?nw=nwusertskorkowski
[7] https://github.com/tskorkowski/crop_yield_prediction_CAS

This LSTM model implementation has approximately 8 million parameters.

Training parameters:

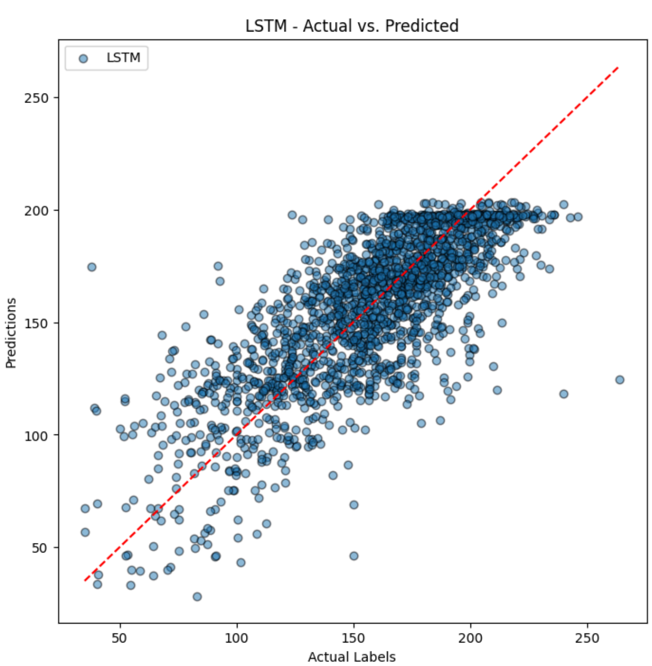
- Learning rate: 0.00013
- 300 epochs with callback monitoring validation loss

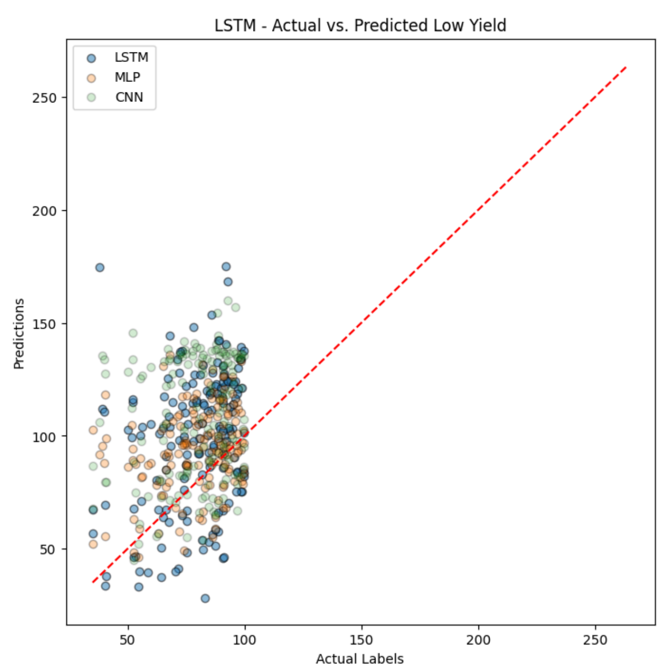
Model performance on test data

Model	RMSE	MAE	Corr
LSTM	24	19	0.777
CNN	26.6	19	0.759
MLP	32.64	22	0.75

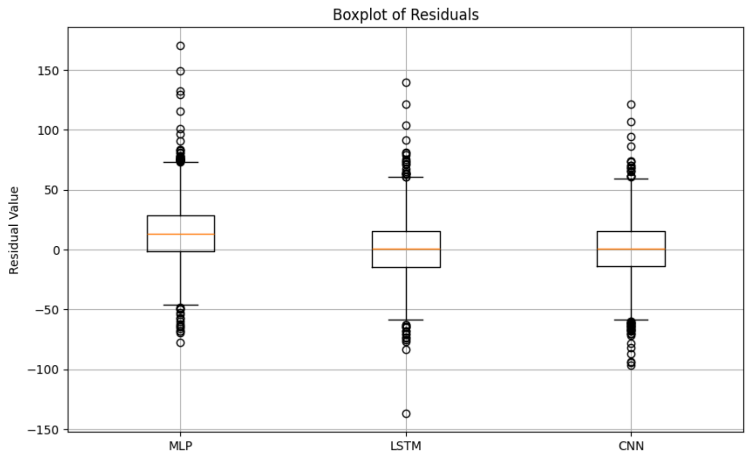
If we take 100 bushels per acre as a low crop threshold then 8.4% or 158 samples fall into that category. Mean squared error for observations below this threshold is the lowest for MLP and equal to 7.45, followed by LSTM and 10.4 and finishing with CNN and RMSE of 12.

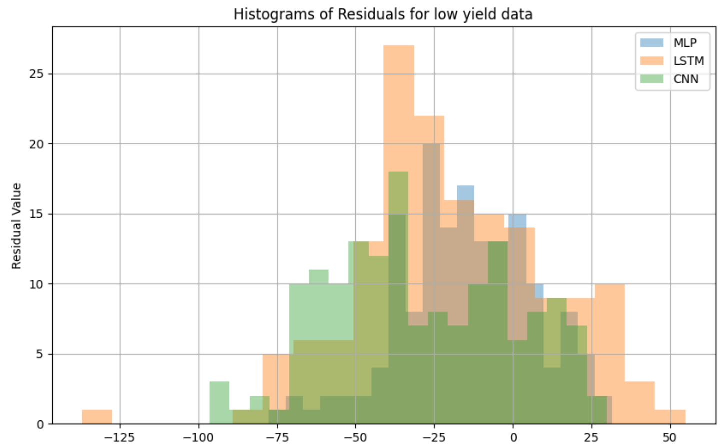
Looking at both residuals and model fit we observe that even though residuals are centered around the zero, all models tend to significantly overestimate low crop yields and underestimate high crop yields. From a practical perspective that means that the models studied are not good enough yet to build an insurance product. This however





could be ratified by relaxing assumptions, collecting more images per year and also including more recent years in the data.





With current models benefit payments would only sometimes be made to those who need it. MLP, the best performing model in the left tail correctly predicts low yield threshold only in 50% of cases.

Since authors of reference study work with soybean crops instead of corn we lack direct ability to compare results. Nevertheless, qualitatively it seems that our models perform significantly worse. Among other things, this could be due to difference in channels captured by MODIS satellites or due to difference in temporal data - data analysed in the paper ends prior to 2017 where our dataset starts. Similarly the authors were interested mostly in average prediction error rather than specific behavior in lower quantiles. Having said that, the obtained results further confirm the value of satellite images as a data source and serve as a starting point for future investigations.

Next steps

The results obtained so far seem to indicate that there are multiple options on how to take this work forward. One way would be to capture higher resolution data. Due to time constraints this was impossible for this project but resolution can easily be increased to 10x10m or 20x20m meters, depending on the channel. Furthermore, the impact of capturing more satellite images per year and data augmentation techniques could be studied in the future.

Another natural extension to the current work would be to apply CNN directly to the images instead of histograms. Also, reduction of a research question to classification problem could be more beneficial from the perspective of building a simple insurance product.

Yet another attractive idea would be to replicate the two prospective papers mentioned in the literature discussion. That approach not only uses more recent model architecture but takes advantage of multiple data modalities as well.